國立交通大學

資訊學院資訊科技（IT）產業研發碩士班

碩 士 論 文

使用無線觸發器之室內特徵定位系統研究

A "Room-Based" Localization System Using Wireless Triggers and Pattern Matching Techniques

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摘 要

根據統計上顯示，人們大部份時間都在室內活動，在越發達的國家中，此現象越明顯。這使得室內人們對定位系統的需求更加強烈。然而，室內的環境比室外更加複雜，訊號更難以追蹤處理。本文基於樣本比對的技術提出了一個以房間為單位的室內定位系統。在本系統中，主要引入無線觸發器的使用，將無線觸發器安裝在房間的出入口或是兩區域間的分界處。利用在伺服器端所接收到回饋的觸發訊息，來達到房間控制和鎖定的效果。同時可以藉由避免長距離的錯誤資訊來大量減低誤差。因此，我們的系統比現行的系統更能準確地判定定位區域。在模擬和實驗的結果中，在多種環境下，我們的系統都有很好的表現。

關鍵詞：廣播，整合傳送，IEEE 802.15.4，無線感測網路，ZigBee。

A "Room-Based" Localization System Using Wireless Triggers and Pattern Matching Techniques

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Abstract

According to statistics, people, especially to those living in developed countries, spend most of their time inside buildings. This has attracted a lot of interest in indoor positioning systems. However, indoor environments are more complicated and difficult to track. This paper proposes a room-based localization system based on pattern-matching techniques. In addition to wireless beacons, we propose a special device called *wireless trigger* that can be deployed at entrances or boundaries of logical areas. Our scheme works by first identifying logical area and then estimating positions in these logical areas according to the transitions of received wireless triggers. Our system therefore improves over existing systems by more accurately identifying logical areas of objects. Finally, simulations show that the proposed location estimation system performs better in different environments compared with the existing methods.

Keywords: broadcast, convergecast, graph theory, IEEE 802.15.4, wireless sensor network,

ZigBee.

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Many people have helped me with this thesis. I deeply appreciate my thesis advisor, Dr. Yu-Chee Tseng, for his intensive advice and instruction. Dr. Seng-Po Guo and Chi-Chung Luo also give me a lot of guidance. I would like to thank all the classmates in High Speed Communication & Computing Laboratory for their invaluable assistance and suggestions. During this time my girlfriend Tzu-Ying Lee has given me a lot of encouragement. The support by the Fontal Technology also grateful acknowledged.

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Chapter 1

Introduction

Wireless Sensor Networks (WSNs) have an endless array of potential applications in both military and civilian applications, including robotic controlling system, battlefield surveillance, target tracking, environmental monitoring, managing merchandise and traffic regulation, to name just a few. One common feature shared by all of these critical applications is the vitality of sensor location. In this work, we implement a room-based localization system based on the pattern-matching technique. In the indoor environment, identifying users' located logical area is more meaningful than a precise location specified by coordinate information. Hence, how to correctly estimate users' located rooms is our primary goal. For this purpose, we introduce a new hardware, called wireless triggers, which is capable of wakening up users' badge devices in a limited range. With the help of wireless triggers, we can identify the events of logical area transition. After receiving the triggered events, we begin to determine the most possible target logical area via a statistical mechanism. The rest of this paper is organized as follows. Chapter 2 briefly presents a review of pattern matching techniques. Chapter 3 describe the system environment and architecture. Also, this chapter describe how wireless trigger combine with wifi Pattern-Matching algorithm. Chapter 4 presents our hardware and software architecture. Simulation and experiment results are given in Chapter 5. Finally, Chapter 6 concludes this paper.

Chapter 2

Relate Work

Recently, location-based applications are regarded as one of the most important services in wireless networks [13], [6]. Location tracking is critical to support location-based services. Although GPS [5] has been widely used, indoor localization is still a challenging problem. Localization models can be classified into *angle of arrival (AoA)* [8], *time of arrival (ToA)* [1], *time difference of arrival (TDoA)* [11], and *fingerprint* [2], [3], [4], [7], [9], [10], [12]. In this work, we are interested in fingerprint-based localization systems, such as RADAR [2]. Unlike other propagation-based localization methods, the fingerprint method does not rely on calculating signal fading in an environment but relies on a training phase to learn the signal strength patterns at a set of training locations from pre-deployed beacons in a sensing field. These beacons can be existing infrastructures, such as IEEE 802.11 access points or other wireless signal resources. To position an object, we will compare its received signal strengths (RSSs) against those of the training locations to find a most similar position.

However, because signal fluctuation is inherent to RF systems, fingerprint schemes have their limitation to positioning accuracy. To conquer this problem, [10] presents a probabilistic framework to handle uncertainty in signal strength measurement. Signal variations are modeled by probability distributions. Based on the similar concept, [12] uses recursive

Bayesian filters for localization. Reference [3] adopts a *neural network* model, which is a multi-layer structure with a number of interconnected neurons, to implement its positioning algorithm. This model has a forward and backward propagation mechanism to adaptively assign suitable weights for the connections based on the training samples. Then, this network can take a number of real-valued numbers as inputs and generate a number of real-valued numbers for the neurons in the output layer. Finally, at the positioning stage, RSSs can be fed into the network and the location whose representative neuron has the highest output is the estimated location.

There is not much work focusing on the room-based localization. Without environmental information, such as logical areas, walls, obstacles, and walking paths, the positioning results are prone to have erroneous logical area identification when the users are near to the boundary of an area. Some location tracking techniques can relieve this problem. In general, the authors define the obstacles in the environment and adopt the particle filtering to avoid the moving paths crossing a wall. In our system, we solve this problem in another way. We introduce a new hardware which can give us the events of logical area transfers. Therefore, we do not need to change the pattern-matching algorithm, but just add a room identification mode when a trigger event occurs.

Chapter 3

System Architecture

3.1 Pattern Matching Techniques

Our goal is to identify the room as well as the position inside the room where a person is currently located. Toward this goal, three types of devices are deployed in a sensing field: badges, routers and triggers. To be located, a person has to carry an end device. In order to bring convenience, this device is designed to look like badge. Each badge will periodically transmit a beacon to announce its existence. Each router will receive and forward packets. Trigger is a new device to use in localization system. The properties of trigger are similar RFID, but trigger has more power, more directional signal, and no ID in transmitting message. A periodical 40kHz signal is shot in a few angle (about 15̊). We use trigger to enhance the precision of traditional localization system and operate the frequency of transmitting packets to reduce decision time and save power.

Room-based localization system works as follows. We are given a set of *active beacon packets* $P = \{p_1, p_2, \ldots, p_n\}$, p_i is broadcasted from the badge (a mobile device) periodically in a sensing field $\mathcal{F} \subseteq \mathbb{R}^2$, and a set of known training locations $\mathcal{L} = \{\ell_1, \ell_2, \ldots, \ell_m\}$ also in $\mathcal{F}$. The system works in two phases. In the *training phase*, at each training location ℓ_i, $i = 1..m$, we measure the signal strength from active beacon packets for a period of time and create a *feature vector* $\boldsymbol{v}_i = [v_{i,1}, v_{i,2}, \ldots, v_{i,n}]$ for ℓ_i, where $v_{i,j} \in \mathbb{R}$ is the averaged RSS from b_j, $j = 1..n$. The feature space of $\boldsymbol{v}_i$ is written as $\mathcal{S} \subseteq \mathbb{R}^n$. The set of feature vectors collected in a database is $\mathcal{V} = \{\boldsymbol{v}_1, \boldsymbol{v}_2, \ldots, \boldsymbol{v}_m\}$. In the *positioning phase*, an object can determine its location in $\mathcal{F}$ by measuring it's RSS vector $\boldsymbol{s} = [s_1, s_2, \ldots, s_n]$ and comparing $\boldsymbol{s}$ against $\mathcal{V}$. The positioning process can be modeled by a map ing function $\mathrm{loc} : (\mathcal{L}, \mathcal{V}, \boldsymbol{s}) \mapsto \mathcal{L}$, whose goal is to determine the location of the object in $\mathcal{L}$. For example, in given $\boldsymbol{s}$, it is suggested to define a distance function h:

$$h(\ell_i) = \|\boldsymbol{s}, \boldsymbol{v}_i\| = \sum_{j=1}^{m} \sqrt{(s_j - v_{i,j})^2}. \tag{1}$$

Then the positioning result $\mathrm{loc}(\mathcal{L}, \mathcal{V}, \boldsymbol{s}) = \arg\min_{\ell_i \in \mathcal{L}} h(\ell_i)$.

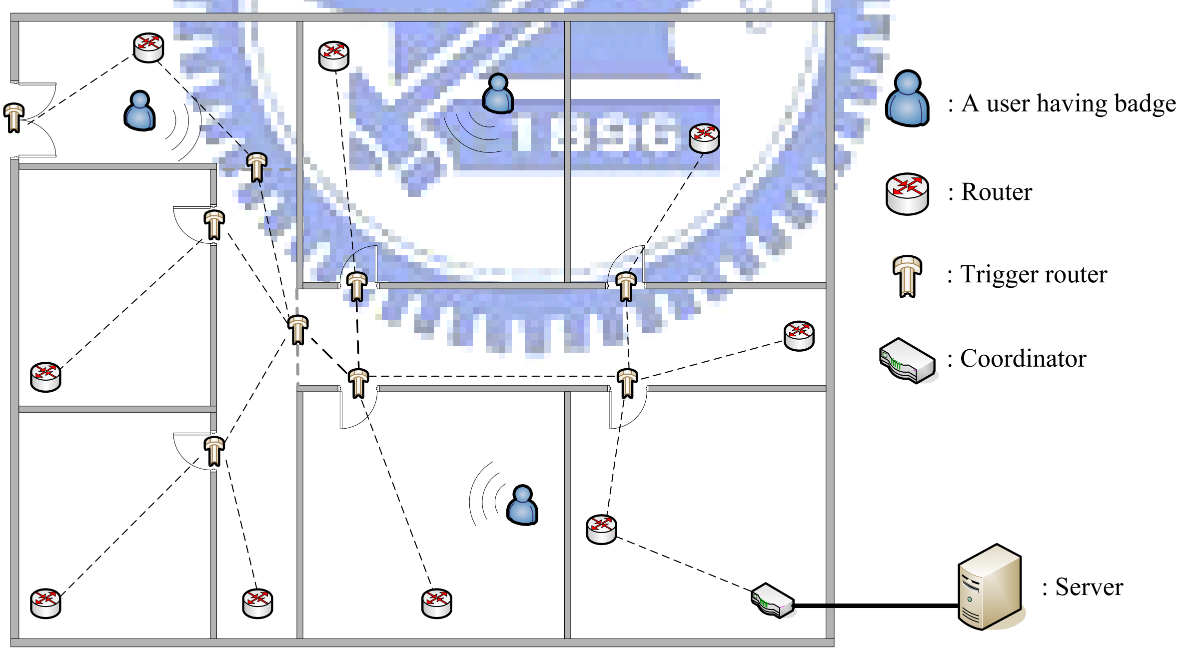


Fig. 1. The environment of room-based localization system

To achieve room-based localization, we are not only given a set of active beacon packets and a set of training locations, but also have the definition of logical areas and a set of triggers which are placed at the locations connecting logical areas. In real environment, we will set trigger in suitable place to design logical areas. For example, doors, boundary of long corridor are general position to be installed. For the ideal case, all logical areas will have the same area.

A trigger event will occur when a user's badge pass through a wireless trigger's sensing area. The trigger event will incur an *Trigger decision mode* which contains a serious of signal strength observations, as shown in Fig. 2. These observations will be used to identify the trigger where the user will be. After the trigger decision mode, we will enter into *Room identification mode*. In room identifying mode, we contain a serious of signal strength observations and use trigger ID to determine which target logical area where the user will be. After the room identification mode, we will switch back to the *Normal positioning mode*. In this mode, we will apply the pattern-matching localization but only those training locations in the identified logical area are evaluated to determine the estimated location of the user.

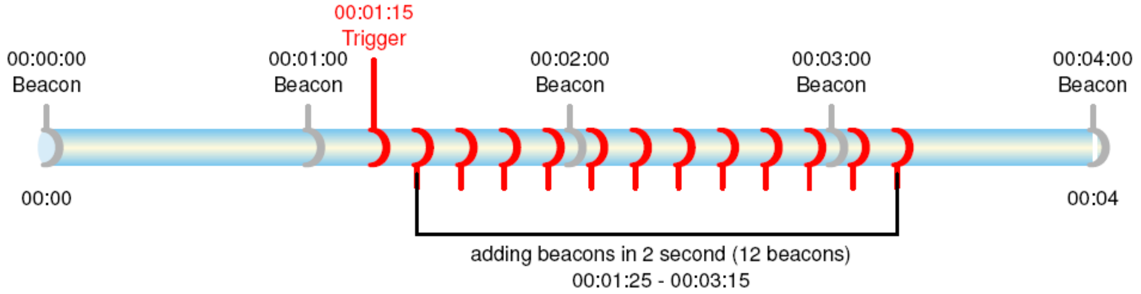


Fig. 2. An example of the events received at a badge side

3.2 Room-Based Localization System

Our objective is to conduct room-based localization. So the primary goal is to increase the possibility of correctly identifying the logical area where a user is located, and the secondary goal is to identify the user's physical location inside that logical area. To achieve these goals, we leverage trigger events and control the frequency to locate a user inside a logical area.

Our scheme works as follows. We design three positioning mode in our system: *Normal positioning mode*, *Trigger decision mode and Room identification mode*.

In *Normal positioning mode*, we use general pattern matching algorithm to determine user's position in logical area. The region of positioning nodes will be restricted in a room. We close the doors to lock users in a logical area. So, all of positioning results are in one room and no one out of the door. The active beacon packet transmitting rate will be slowed down in badge. Low positioning frequency is not to influence the room-based localization result, but it can help us to save power cost.

Trigger decision mode will be arisen from a trigger event. When a trigger is occurred, room-based localization system leaves from *Normal positioning mode* and enters to *Trigger decision mode*. In *Trigger decision mode*, we collect a few active beacon packets to determine what wireless trigger causes the trigger event occurred. There are many trigger decision methods for us to determine the event trigger. The closest one to be chosen, similar fingerprint to use and tracking prediction are some methods for us to use. In this work, we choose the router which has maximum signal strength to determine trigger router's position. In order to reduce the time of *Trigger decision mode*, we increase active beacon packet transmitting rate in badge to let us can collect enough data in less time.

In *Room identification mode*, we got event trigger in *Trigger decision mode*, so we search the corresponding relative map to get room information. We look up a relative map to obtain the logical areas connected by this wireless trigger. The relative map is a topography which consists of a set of blocks, nodes, and edges. A block, which substitutes a logical area, is connected to another block by a node, which substitutes a wireless trigger, by an edge. In other words, there is no two blocks connected together directly. The next two figures show an example. Fig. 3 is the floor plan and Fig. 4 is the corresponding relative map.

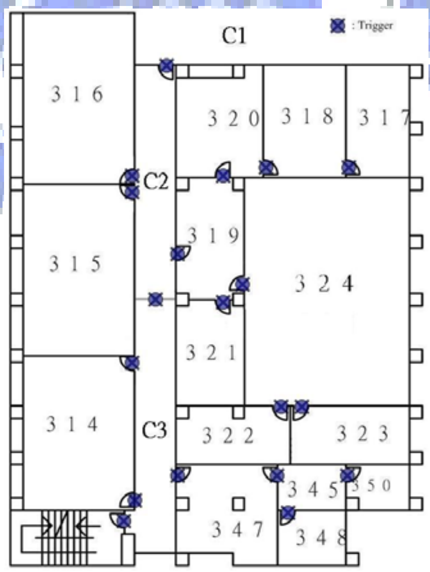


Fig. 3. The floor plan at the 3F, Engineering Building III, National Chiao Tung University

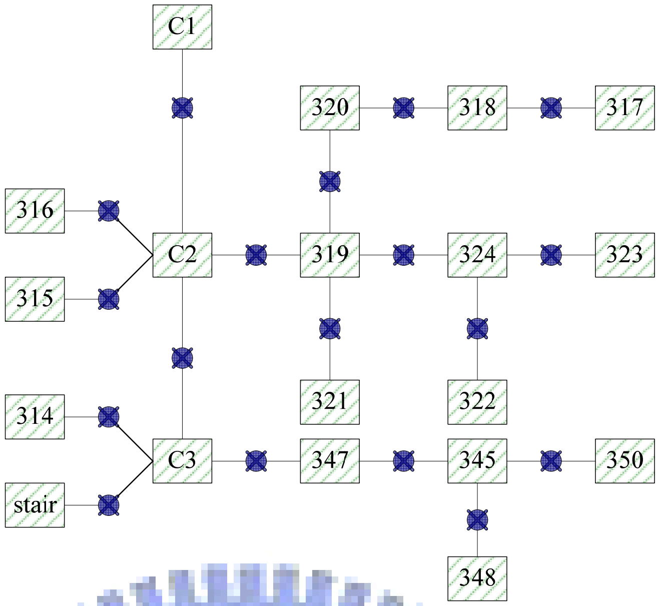


Fig. 4. The corresponding relative map at the 3F, Engineering Building III, National Chiao Tung University

Finally, we can collect a serious of signal strength observations in a short period of time. The locations of these observations will be estimated by the location server. When identifying logical areas, we only evaluate the patterns of those training locations within the restricted logical areas obtained from the relative map. The restricted pattern-matching localization can reduce the computation cost while increase the distinction of patterns of logical areas so as to improve the possibility of identifying logical areas. The estimated locations will be used to decide the most possible logical area. There are many ways to implement this decider. In our current status, we adopt a simple majority voting strategy. After identifying a logical area, we switch back to the *Normal positioning mode* and restrict the pattern-matching localization to search the training location in this logical area only.

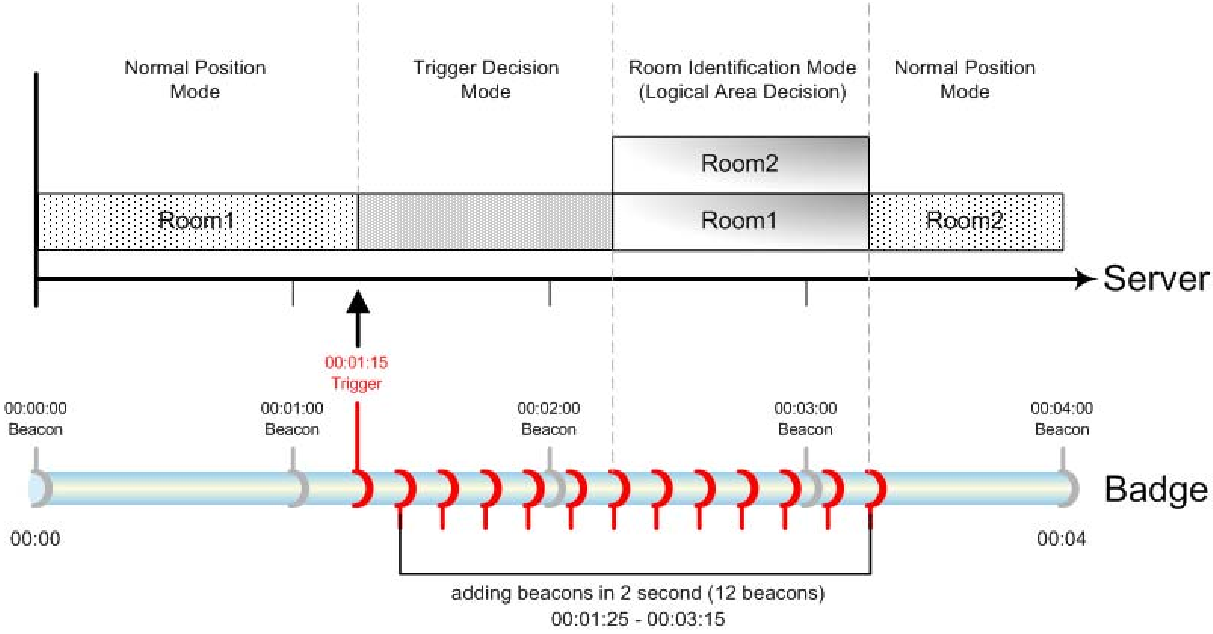


Fig. 5. An example of the events received at a badge side and server side

Fig. 5 shows an example of the events received at a badge side and server side in four seconds. In this figure, a badge broadcasts one active beacon packet per second periodically. At time 00:01:15, a trigger event is observed and we switch to the *Trigger decision mode* to determine which wireless trigger will be triggered. In this example, there are 12 additional active beacon packets generated in 2 seconds. First 6 active beacon packets are used by *Trigger decision mode* and last 6 active beacon packets are used by *Room identification mode*.

For example, in Fig. 6, if users want to move from room-316 to room-324, they will pass through corridor-C2 and room-319. There will be three trigger events. When the first trigger event is occurred, we switch to the room identification mode. Hence, we identify the closest wireless trigger first. In normal case, we can determine the trigger event is from trigger, and then we could infer the possible logical areas which the users located in are corridor-C2 and room-316. After the trigger event, we will obtain a number of signal strength observations in higher frequency. We then gather the statistics of the estimated locations and decide the most possible one, such as the correct corridor-C2. When deciding the target logical area of the first trigger event, we will close the connections and switch back to the normal positioning mode so the following location estimations will be restricted in corridor-C2. When the second trigger event is occurred, we open the connections again and repeat the room identification process as above. Fig. 7 is an illustration of the mode switching in the proposed room-based localization system.

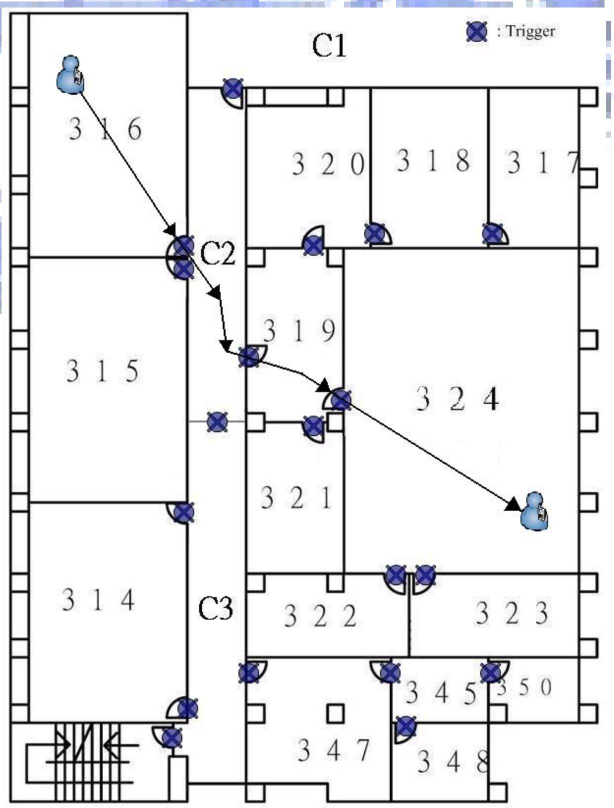


Fig. 6. The path of a user goes from R316 to R324

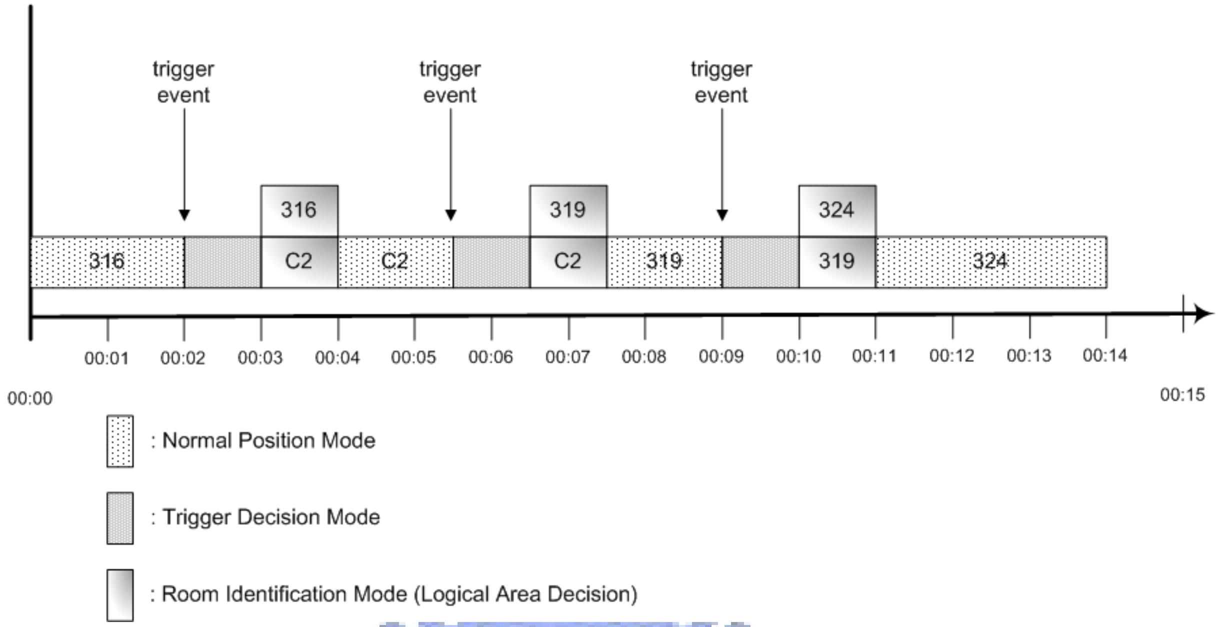


Fig. 7. An illustration of the mode switching in the proposed room-based localization system

Chapter 4

Implementation

4.1 Hardware Architecture

The Room-based Location system using trigger in ZigBee network is established to analyze the pattern matching method's efficiency in ZigBee Network. Adding trigger units make our system having more accuracy in special environment. We use Fontal's FT-6300 iTracer Easy Kit to develop this system. It's a experimental tools using in sensor network researching. Tree main components comprise the Room-based Location system: Coordinator, Router node and Badge.

IEEE 802.15.4 is allowed to establish in December, 2000 and they are allowed to be a standard in October, 2003 by IEEE. IEEE 802.15.4 is suitable to transfer in short distance and low rate in upper communicated protocol. The standards of Mac layer, application programs, interface and physical layer are ordered by ZigBee alliance. ZigBee alliance and IEEE research together and cooperate to product a standard network platform.

The advantage of ZigBee/IEEE 802.15.4 are :

- Saving more power
- A flexible network structure
- Low complexity to design in hardware and software

- High reliability for data transferring
- Data latency can be controlled
- Permitting to use different secure levels

The FT-6300: iTracer Easy Kit is an experimental tool to supply college and researchers to analyze sensor network system. The FT-6300 is produced by Fontal technology incorporation and all of it's components are high power ZigBee modules. It's based on the Jennic JN5121 with 16MHz 32-bit RISC CPU, 96kB RAM and 64kB ROM. The Jennic JN5121 includes 4-input 12-bit ADC, 2 11-bit DAC, one temperature sensor, two application timer/counters, three system timers, two UARTs, 21 GPIO, 5 SPI port to select and 2-wire serial interface. The special design of FT-6300 is trigger. The node with trigger can transmit a 40KHz signal and receive it. A trigger signal can be detect correctly in 2m. ZigBee system works in 2.405GHz~2.480GHz to distinguish into 16 channels. Antenna is another different design in FT-6300. There are dipole and plat antennas to let us to choose in different environment. Maximum transmission distance is 700m in outdoor, but there are very barriers in indoor, multi-path and power decay make very critical influence, 15-100m is a reliable transmission distance. A picture of the FT-6300: iTracer Easy Kit is shown in Fig. 8.

Fig. 8.　　FT-6300: iTracer experimental tool kit

All of devices are based on FT-6300 platform (Fig. 9). To modify some functions from hardware and software, we can let them to have different roles. It is an introduction to show main devices in our system at follows.

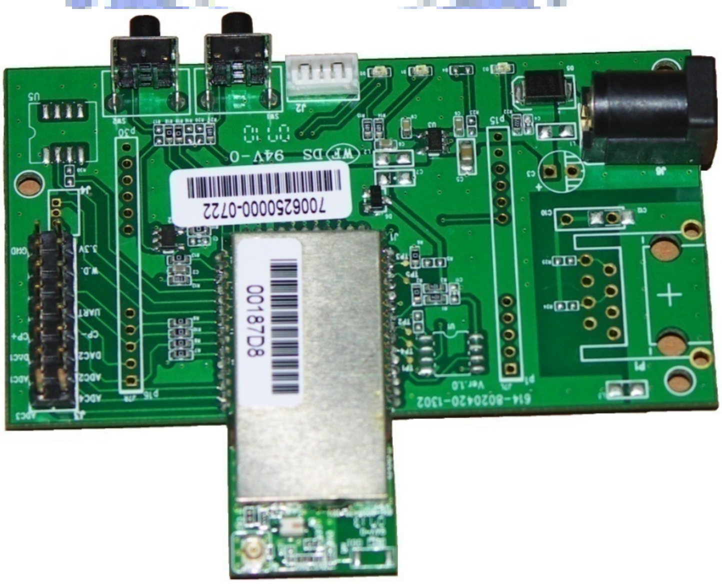


Fig. 9.　　A basic FT-6300 platform

- Coordinator

Coordinator is the most important device in the network. In routing algorithm, it calculates and assigns address to build a mesh routing network. It also plays a role of gateway. It collects all packets from badges and routers and sends them to server from RS-232 or Ethernet. When user wants to send commands to any device, it needs to transmit through coordinator. The coordinator device is shown in Fig. 10.

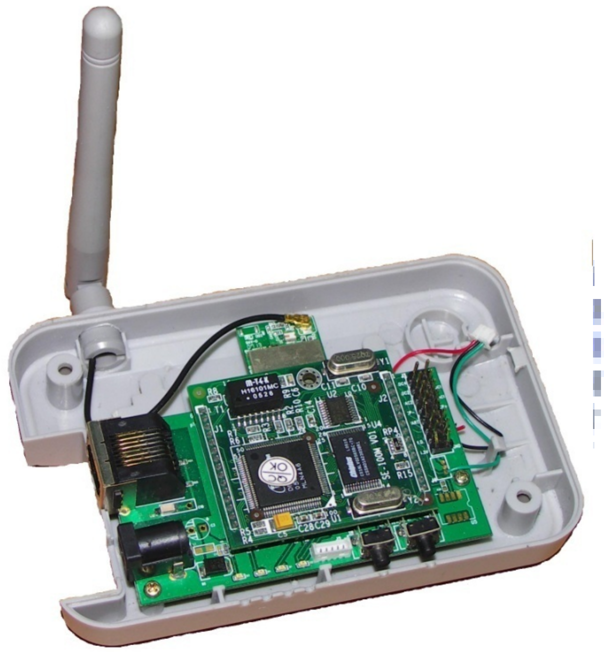


Fig. 10. The hardware of Zigbee wireless sensors: coordinator

- Router

Routers are basic nodes in our ZigBee network. A router receives packets from Badges or another routers and sends packets to coordinator through a better path. There are many solutions for us to build a mesh network and choose a nice path in ZigBee. Now, we use

“Self-Learning Routing” to develop our routing system. “Self-Leaning Routing” is a new routing method in ZigBee network that be developed by HSCC library. The router device is shown in Fig. 11.

Fig. 11. The hardware of Zigbee wireless sensors: router

- Trigger

In order to increase the locating accuracy, some of routers are equipped trigger. The trigger broadcasts a 40kHz signal periodically. The trigger often sets in the top of a door and emits the signal downward. When someone wears a badge through the door, the badge will be woken up by trigger and broadcasts a packet to tell everyone him is triggered. Certainly, trigger routers still do all works that general routers can do. The trigger device is shown in Fig. 12.

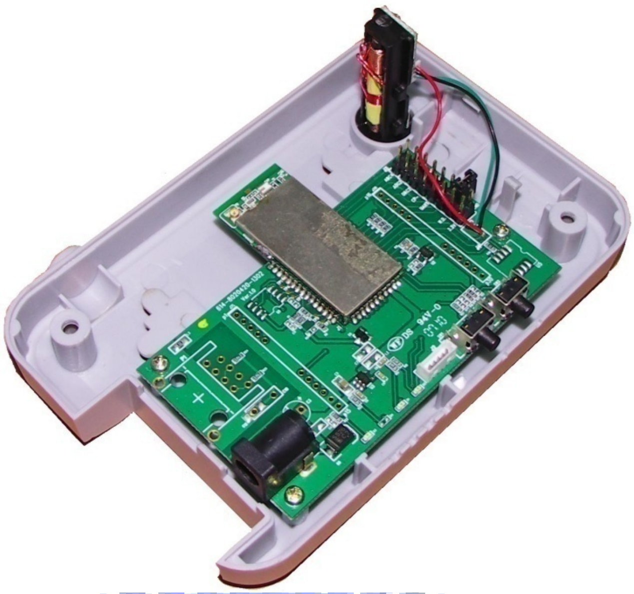


Fig. 12.　The hardware of Zigbee wireless sensors: trigger

- Badge

Badge is a personal device. In order to increases the convenience. Decreasing volume, saving energy are our targets to design the badge. The badge is thin, and likes a credit card. To differ to general location system, actively and periodically broadcast packet is our special design to save energy. Every badge has a small trigger to detect trigger signal. The badge device is shown in Fig. 13.

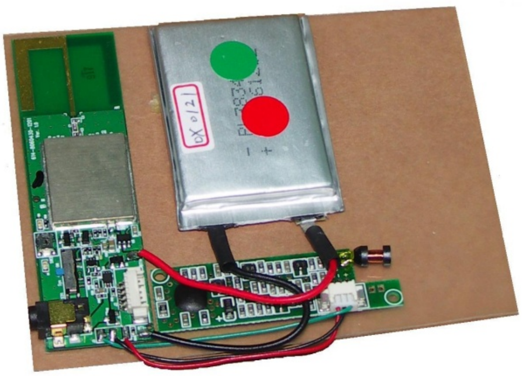


Fig. 13.　The hardware of Zigbee wireless sensors: badge

4.2 Software Architecture

We will introduce our system architecture in this chapter. The diagram is shown in Fig. 14.

Badges, routers, coordinator and location server are our main components of the system. All of components are developed by FT-6300 platform, but they do different actions in their roles. Badges are carried by users. In addition to trigger, the badge doesn't receive any signal. It only broadcasts a hello message to neighbor device periodically. When the badge is triggered by a trigger signal, it will wake up and send a packet to let everyone to know it is triggered. By way of this mechanism, badges can save power.

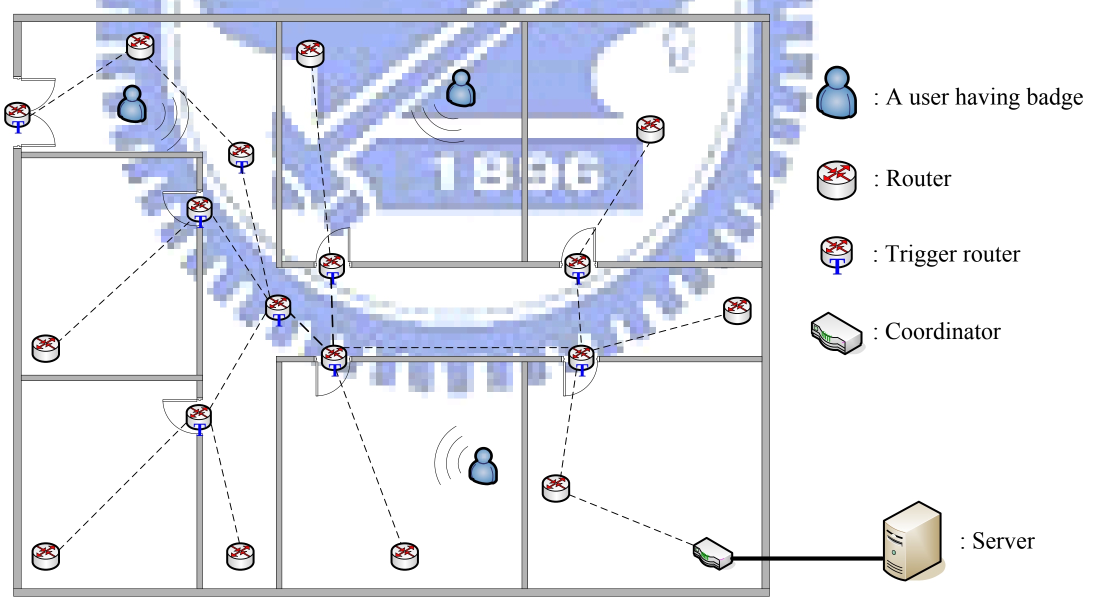


Fig. 14. An example of the system architecture

A router receives many wireless signals from his neighbors. By collecting all data, we can make a neighbor in router. Using “Self-Learning Routing” algorithm, the system builds all routing path from coordinator to every routers. Regardless of sending message to coordinator or giving orders to routers, all packets are transferred to follow the topology. Coordinator gets all data and arranges them for the fixed format and send to location server. Translating the sequence from coordinator to run real time location and sending some commands to routers do special work are server’s work. The server connects to coordinator by Ethernet, because we need a stable and large transmission rate to support a great deal of data transferring. The simple data follows chart is shown in Fig. 15.

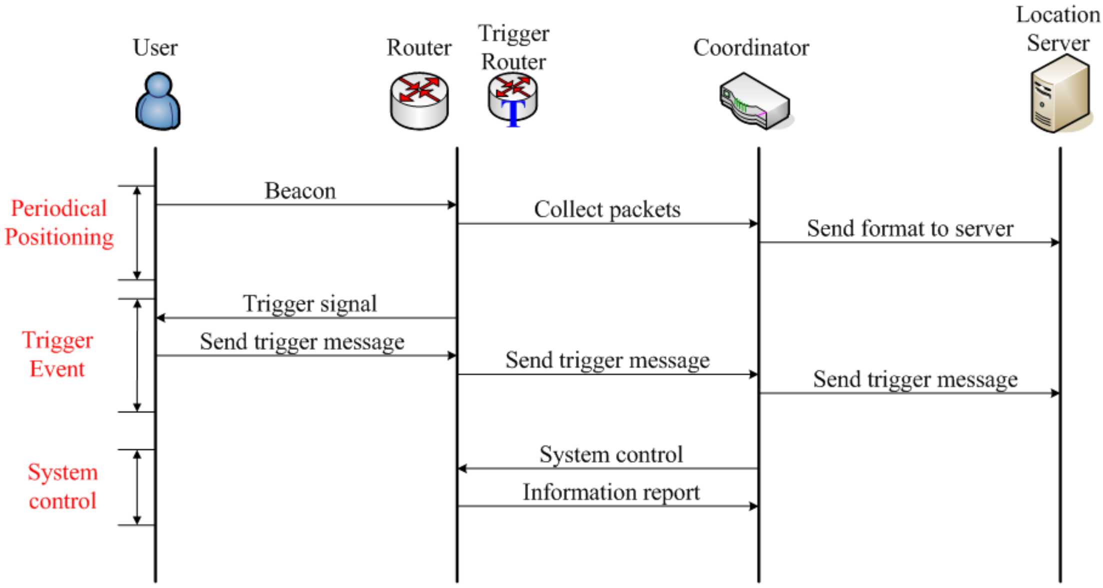


Fig. 15. The message flowchart

Chapter 5

Simulation and Experiment Results

5.1 Simulation

In this chapter, we conduct some experiments to evaluate the performance of the room-based localization system. We study the impact of varying parameters used in our system.

5.1.1 RIM Model

Radio irregularity is a common and non- negligible phenomenon in wireless sensor networks. It is a large influence on location system. Because it makes the signal strength is hard to collect, but the influence sometimes can help us to improve position accuracy in special case. For example, we can use WAF (wall attenuation factor to simulate barriers. Therefore, we use RMI to reduce noise and improve accuracy in special environment.

The spherical radio patterns assumed by simulators may not approximate real radio properties well. Radio Irregularity Model (RIM) bridges the gap between spherical radio models and physical reality.

In isotropic radios model, the received signal strength is usually represented with the following formula:

$$Received\ Signal\ Strength = Sending\ Power - Path\ Loss + Fading \quad (2)$$

Because the radio model is non-isotropic in real environment, we use Degree of Irregularity (DOI) to emend isotropic radio models. We adjust the value of path loss models in Equation 1 based on BOI values, resulting in the following formula:

$$Received\ Signal\ Strength = Sending\ Power - DOI\ Adjusted\ Path\ Loss + Fading \quad (3)$$

$$DOI\ Adjusted\ Path\ Loss = Path\ Loss \times K_i \quad (4)$$

Here K_i is a coefficient to represent the difference in path loss in different directions. Specifically K_i is the i^{th} degree coefficient, which is calculated in the following way:

$$K_i = \begin{cases} 1 \ , & i = 0 \\ K_{i-1} \pm Rand \times DOI \ , & 0 < i < 360 \ \wedge \ i \in N \end{cases}$$

$$where \quad |K_0 - K_{359}| \leq DOI \quad (5)$$

In RIM, the variance of sending power follows a normal distribution. So we use Variance of Sending Power (VSP) to define as the maximum percentage variance of the signal sending power among different devices.

$$VSP\ Adjusted\ Sending\ Power = Sending\ Power \times (1 + Rand \times VSP) \quad (6)$$

With the two parameters: DOI and *VSP*, the RIM model can be formulated as follows:

$$Received\ Signal\ Strength = VSP\ Adjusted\ Sending\ Power - DOI\ Adjusted\ Path\ Loss + Fading \quad (7)$$

Then we can extend the formula to use in our simulation. We increase the PL_{obs} in the formula to simulate wall's influence in indoor. C is the maximum of walls up to which the attenuation factor makes a difference. nW is the number of walls between the transmitter and receiver. WAF is wall attenuation factor (derived empirically).

$$PL_{obs} = \begin{cases} nW \times WAF & , \quad nW < C \\ C \times WAF & , \quad nW \geq C \end{cases} \tag{8}$$

5.1.2 Simulation Model

Figure X is shown our simulated environment. We consider a 100×100 square sensing field. Since larger environment results in larger differences between different methods, we simply perform reasonably scaled simulations to observe the trend of the results. Twelve routers are placed at (5, 5), (40, 5), (60, 5), (95, 5), (5, 40), (95, 40), (5, 60), (95, 60), (5, 95), (40, 95), (60, 95) and (95, 95), respectively. Sixteen rooms are placed in simulated environment. The length and width can be signed in figure X. In 10000 grids, we collect 100 training samples at each of them in the training phase. The log-distance path loss model is exploited to model the signal propagation given by Equation (9):

$$PL(d) = PL(d_0) + 10\alpha \log\left(\frac{d}{d_0}\right) + N(0,\sigma) \tag{9}$$

Where $d_0 = 1$ is the reference distance, and d is the distance between the transmitter and the receiver. The term α denotes the path loss exponent, typically from 2 to 6, and $N(0,\sigma)$ is a zero-mean normal distributed random variable with a stand deviationσ. The received signal strengths are generated by P_t-$PL(d)$, where P_t denotes the transmit power. Also, Pt is set to be 15dBm, $PL(d_0)$ = 37.3, α=3.3, and σ=4.

To evaluate the system performance, three performance metrics are employed:

- Positioning error: The error distance between the estimated location and the true location is the positioning error. We will use this metric to evaluate the location accuracy in our room-based localization system.
- Hit rate: To get insight into the impact of room-based on localization, the hit rate is defined as the probability of accurately predicting the true room. Obviously, our system is more reliable when the hit rate is higher.

The above performance metrics are measured by the following steps. First, we use the signal propagation model mentioned in Equation (2) to simulate 5 samples per second in the time of tracking. Our system predicts the positioning room in restricted region, continuously. A hit event occurs when the predicting room and real position is correspondent.

5.1.3 Noise

In Fig. 16 and Fig. 17, we use two scenarios to evaluate the hit rate and positioning error. Scenario 1 walks through the dotted line. It was begun on northwest room and entered into two rooms. Finally, the user stays in one of center room. Scenario 2 is a special case which enters a room and goes a corner of the room. This action helps us to know the positioning node jumping over the wall or not.

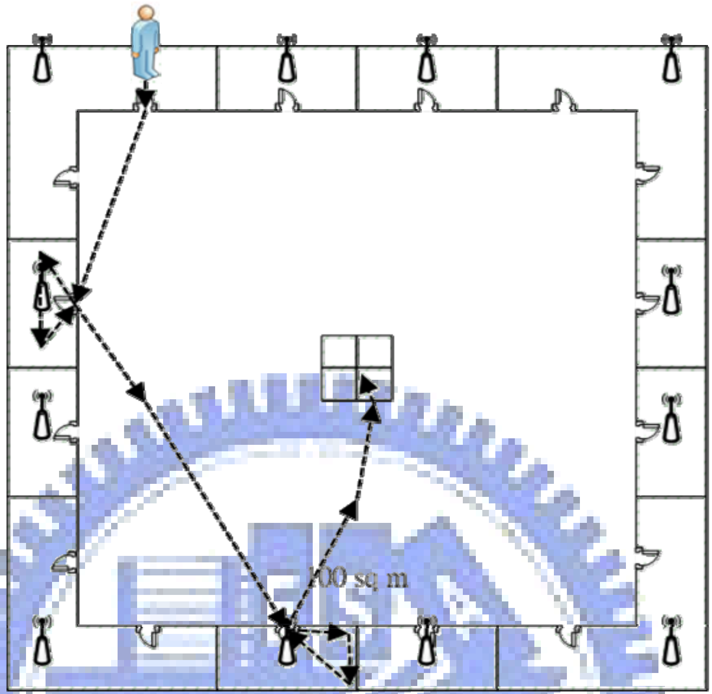


Fig. 16. Simulating Scenario 1

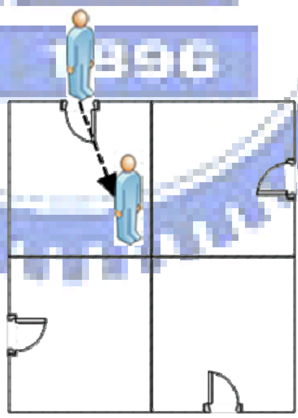


Fig. 17. Simulating Scenario 2

In Fig. 18, we can see that traditional NNSS method and room-based localization system have similar positioning error in different noise. In Fig. 19, NNSS is suitable in lower noise environment. If noise is growing, trigger system helps us to raise the hit rate. According to above observations, our system will have a good hit rate when it works in high power environment.

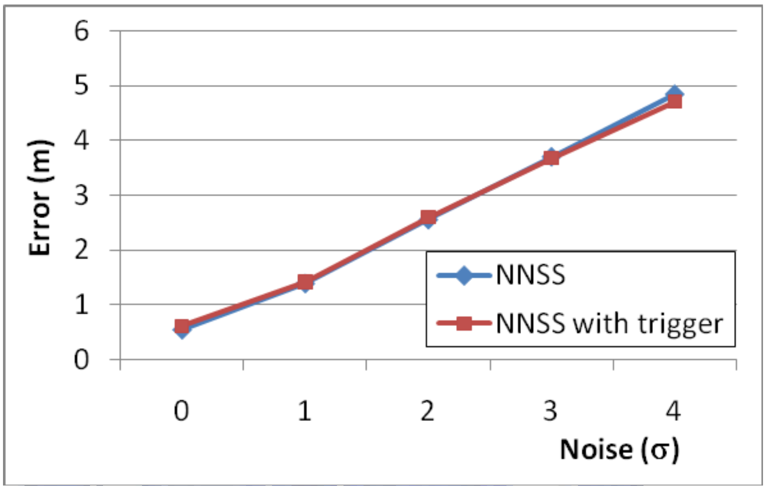


Fig. 18. The error distance in different noise between NNSS and NNSS with trigger at Scenario 1

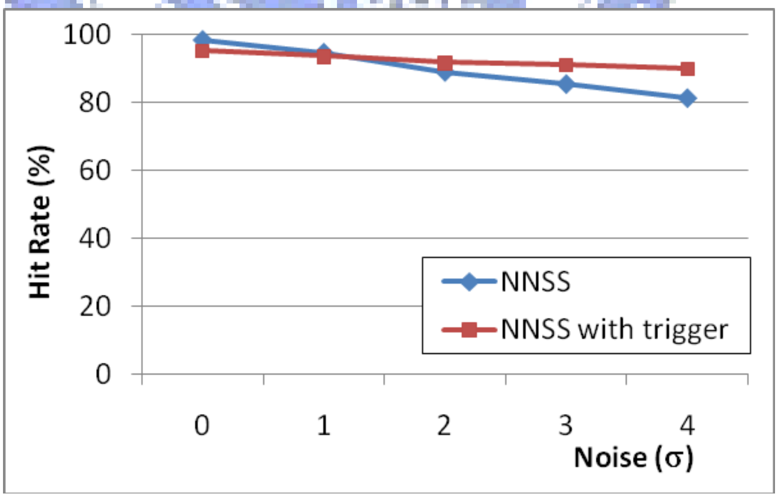


Fig. 19. The hit rate in different noise between NNSS and NNSS with trigger at Scenario 1

Scenario 2 has a special ended point. We set the ended point to close the wall. In Fig. 20, traditional NNSS isn't accuracy when we increase noise, but there is more improvement when we use trigger. The entered room is a small place. It is only 5×5 square meters. If noise is growing, the noise deviation will jump over the wall. It causes easy to position in wrong room. Therefore, we need to control the positioning time in a suitable period when trigger event occurs. In this environment, sampling 10 simples is better than sampling 20 samples in high noise. There is similar phenomenon in Fig. 21. The positioning error of our system is lower than traditional NNSS, but there is high error in NNSS with trigger (t=20) in high noise.

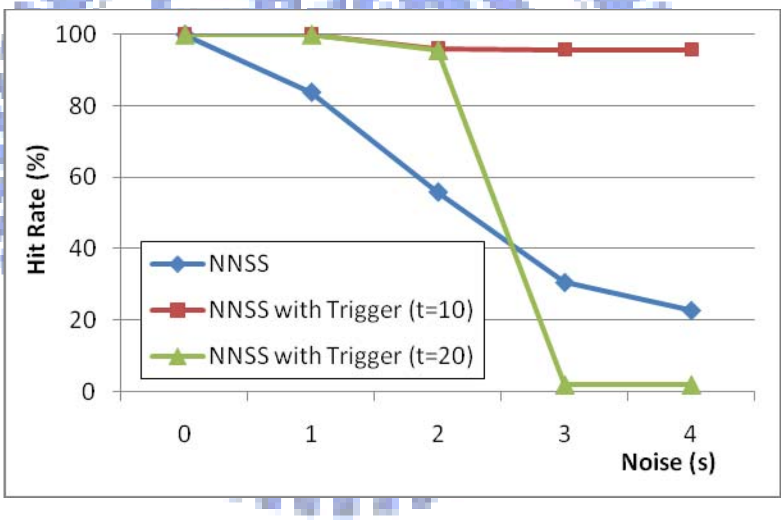


Fig. 20. The hit rate in different noise between NNSS and NNSS with trigger at Scenario 2

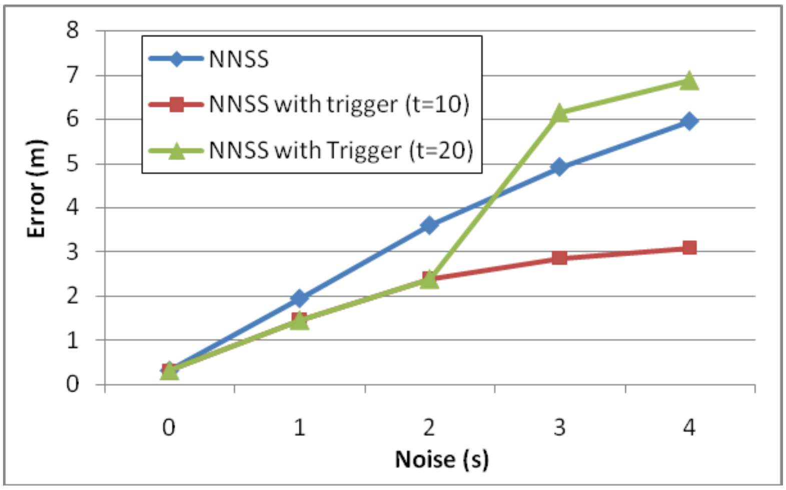


Fig. 21. The error distance in different noise between NNSS and NNSS with trigger at Scenario 2

5.1.4 WAF

In this chapter, we will investigate the impact of wall on hit rate and positioning error. We use the extend RIM (in chapter 5.1.1) to simulate the wall's phenomenon. We also simulate two scenarios the same as above chapter.

Fig. 22 is shown that the hit rate in non-trigger and trigger system when WAF =1 to 5. The hit rate of NNSS with trigger system is more than traditional NNSS system. The hit rate is often higher than 90%. In figure (b), using trigger can also decreases positioning error. The positioning error is to reduce when WAF is added. The reason is more WAF to cause much signal strength decay and the difference is larger.

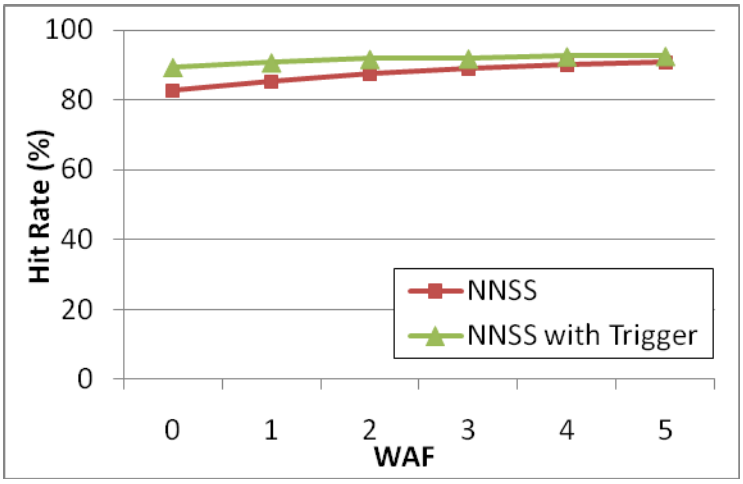


Fig. 22. The hit rate in different WAF between NNSS and NNSS with trigger at Scenario 1

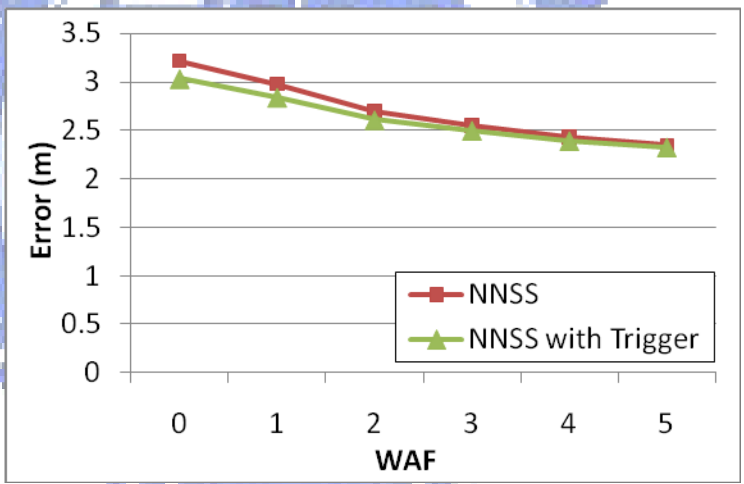


Fig. 23. The error distance in different WAF between NNSS and NNSS with trigger at Scenario 1

In Fig. 24 and Fig. 25, we use scenario 2 to observe the changes of hit rate and positioning error. We can see that hit rate is very low when WAF is lower, especially in trigger system, but when WAF >2, the hit rate of trigger system is better than non-trigger system. The error of trigger system is mostly less than non-trigger system. Some of particular condition is location in wrong room in the twinkling of an eye.

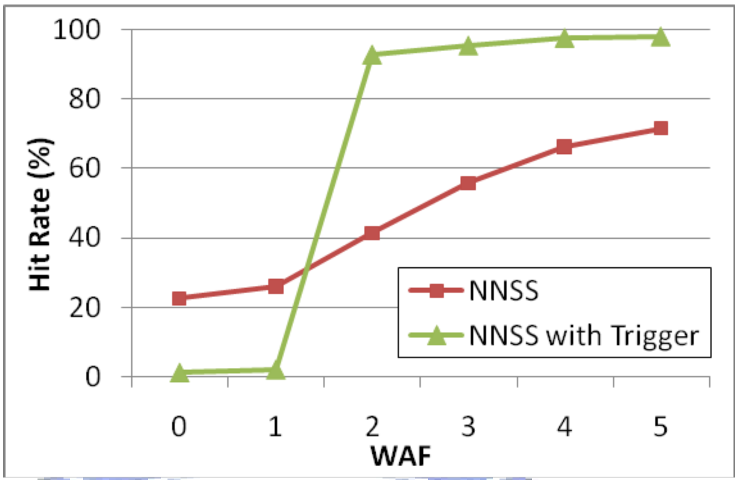


Fig. 24. The hit rate in different WAF between NNSS and NNSS with trigger at Scenario 2

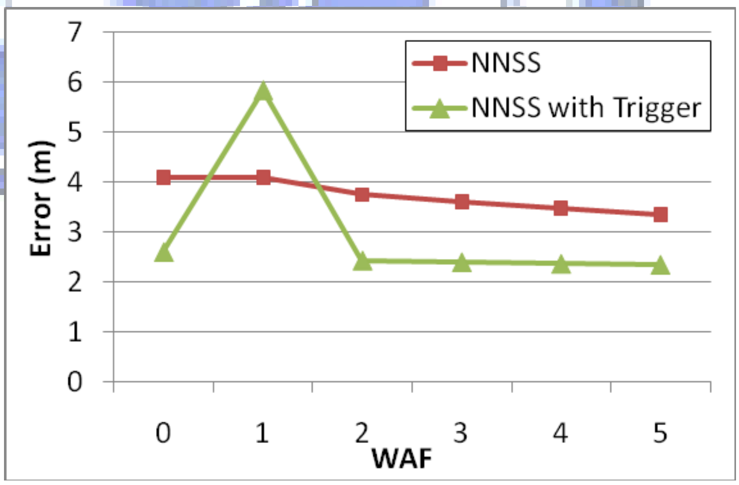


Fig. 25. The error distance in different WAF between NNSS and NNSS with trigger at Scenario 2

In above simulated results, we believe the trigger can increase hit rate and reduce positioning error. When the environment is complex, trigger has much powerful effect. We are sure the room-based location system is an effective design.

5.2 Experiment

In order to prove that the room-based localization system is effective, we make some experiments to our system. The experimental environment is at 3F, Engineering Building III ,National Chiao Tung University. The total area is 23.4×38.2 square meters. There are 12 rooms and one corridor. The partition materials of wall are wood and concrete, mostly. The platform of experimental environment is shown in Fig. 26.

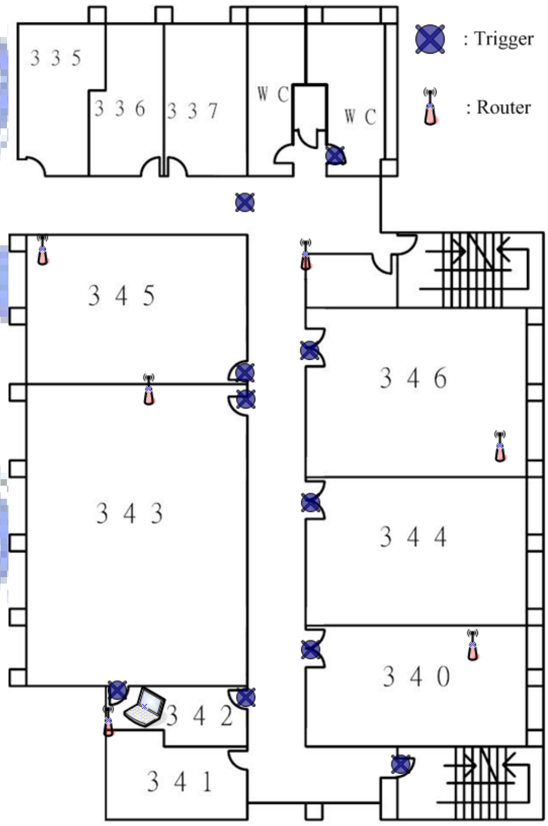


Fig. 26. The experiment environment at 3F, Engineering Building III, National Chiao Tung University

We placed six routers in this environment and installed trigger in each junction of blocks.

In order to assess this environment using pattern matching technique. We move around several times in **aera A** to estimate the localization and observe the distribution of results. The distribution of these points can be seen from Fig. 27.

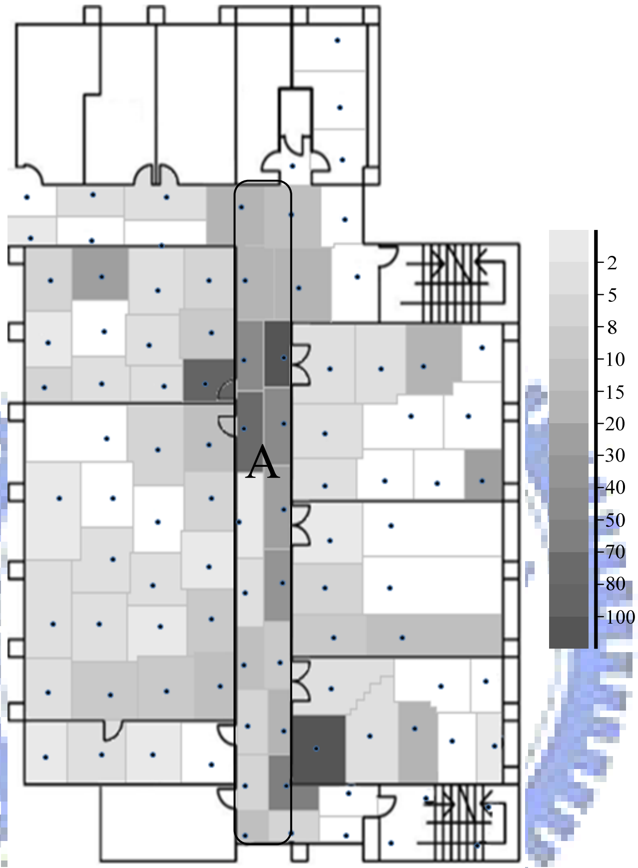


Fig. 27. The predicting distribution of area A

In figure 27, there are 67.0% patterns at are correct areas. We would like to improve the accuracy by using trigger system. If we can determine the transferring of areas accurately, we can use the information of areas to rule out the possibility of some error. At the same time, time complexity.

5.2.1 Moving Test

We design a moving path to show our method. In Fig. 28, a moving path starts from corridor and goes through five rooms (through five triggers). In order to show the steps of moving path clearly, we split in half to Fig. 28. Fig. 29(a) and Fig. 29(b) are the real time position result using NNSS algorithm and our trigger system. The thin line is the result of using basic pattern matching technique to evaluate and the dotted line is the result of using our method to amend. The Fig. 30 shows the detailed differences between these two methods. We can find the corresponding sequence from the labels.

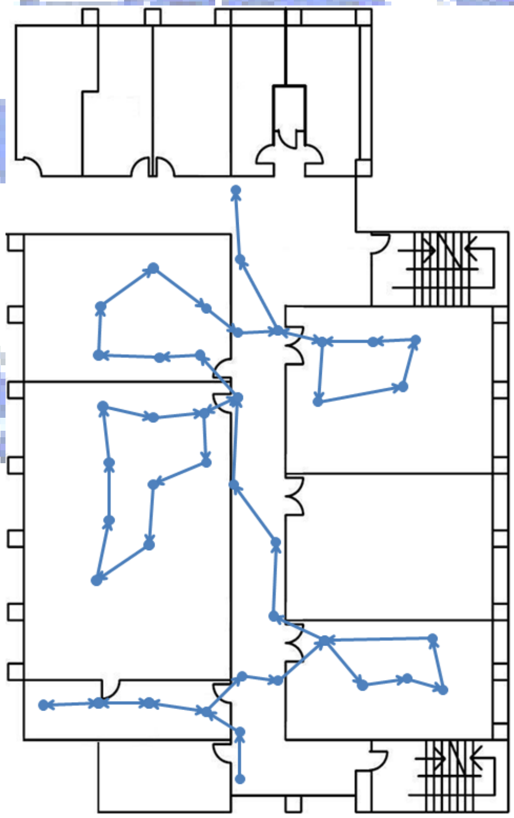
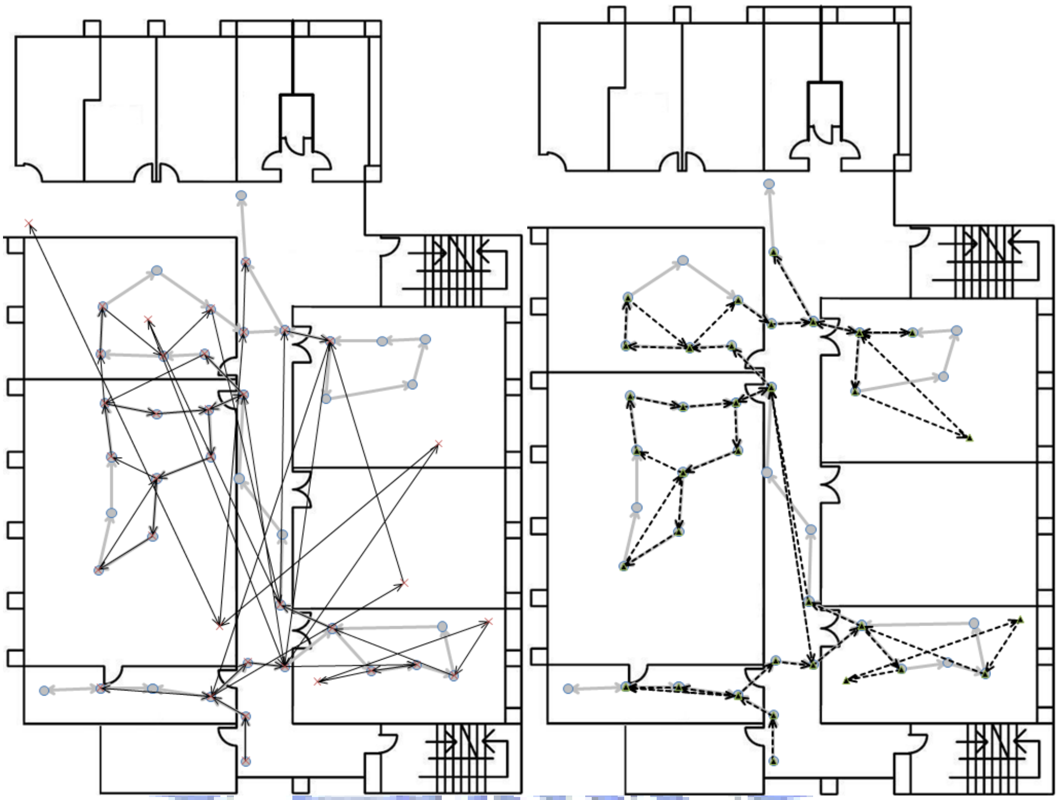


Fig. 28. A test moving path through five rooms

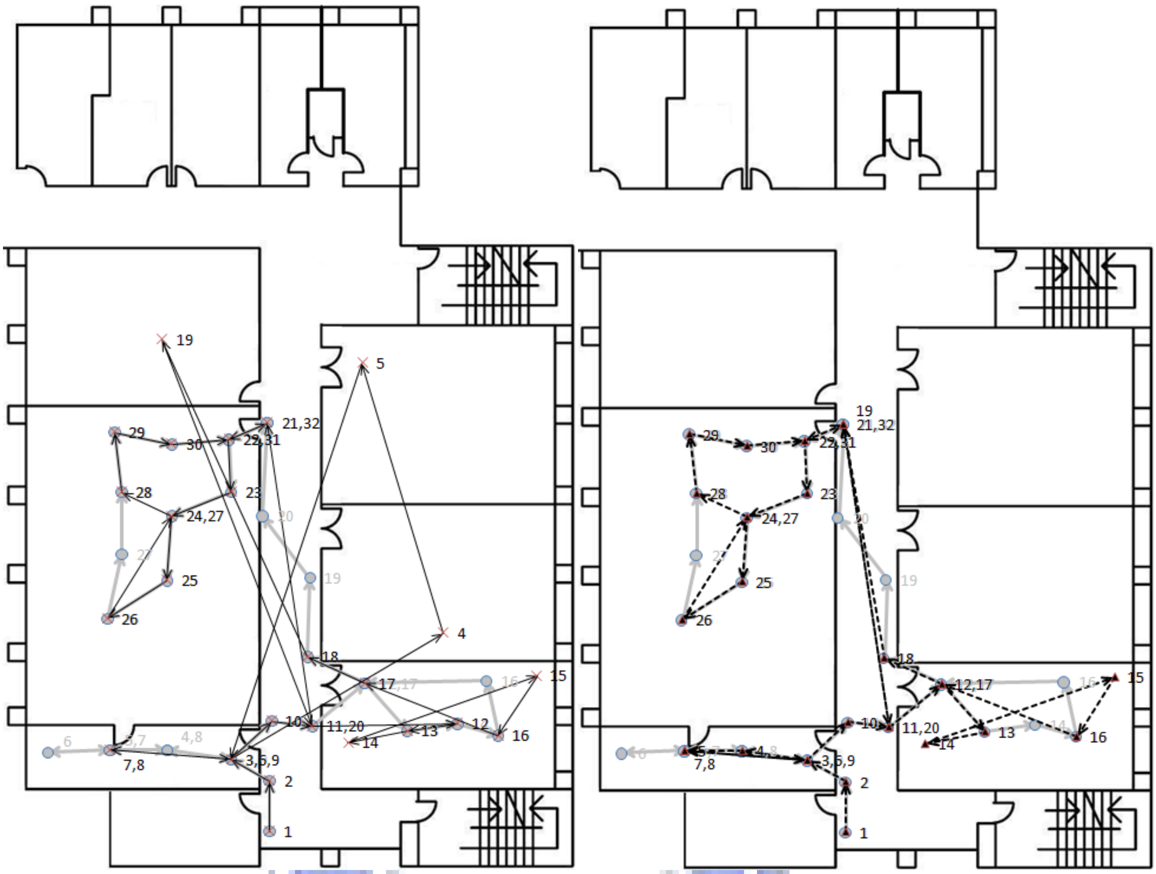


(a). (b)

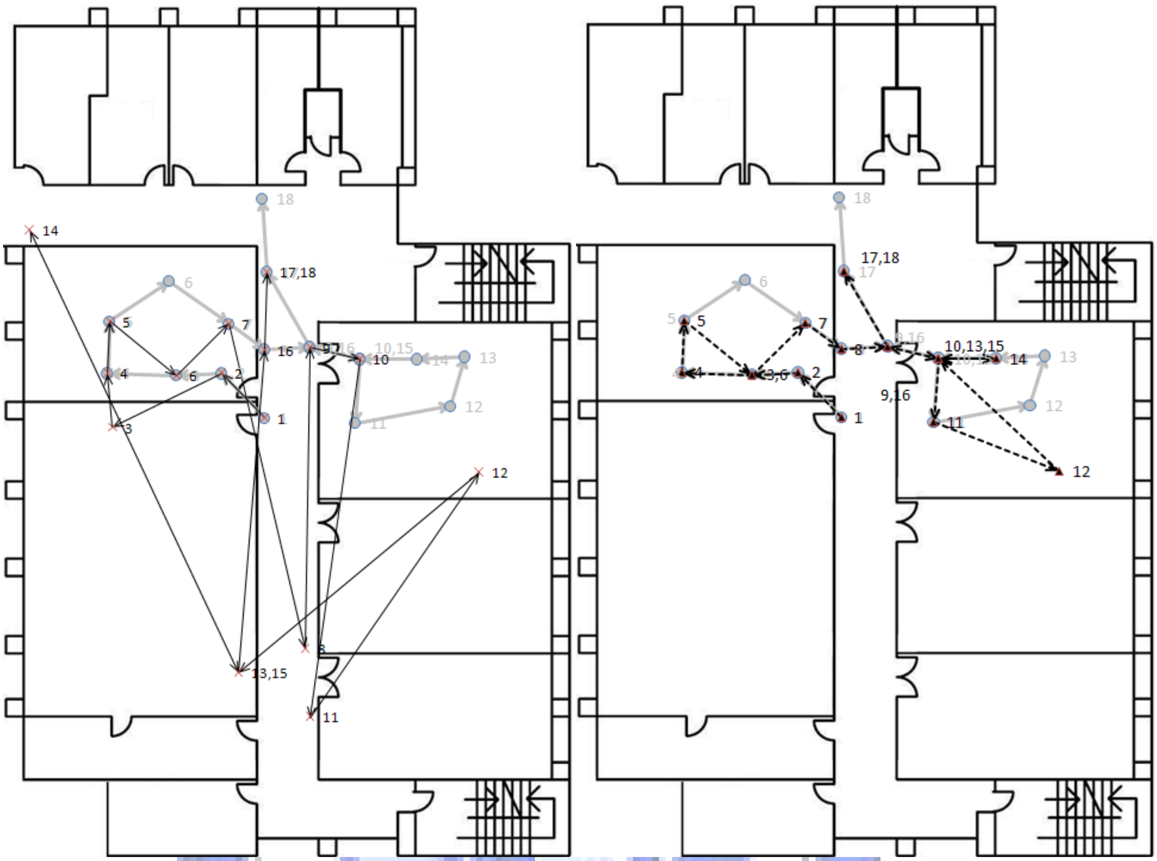
Fig. 29. The graphics of predicting path: (a)NNSS, (b)NNSS with trigger

In Fig. 30(a) and Fig. 30(b), the start point is point 1 and end point is point 32 in lower half of the moving path. Point 4, point 5 and point 19 are obviously incorrect predicting point that be amended. In Fig. 30(c) and Fig. 30(d), the start point is point 1 and end point is point 18 in upper half of the moving path. Point 3, point 8, point 11, point 14, point 15 and point 16 are obviously incorrect predicting point that be amended.

In these four figures, our system locks the moving path in correct area. Although there are some jumps in an area, the degree of jumps is lower and average error distance is reduced, too. There are 49 predicting point in this moving path. When we use traditional pattern matching method (NNSS), the average error distance is 3.49m and the hit rate is 84%. When we use our system, the average error distance is reduced to 1.90m and hit rate is increased to 100%.



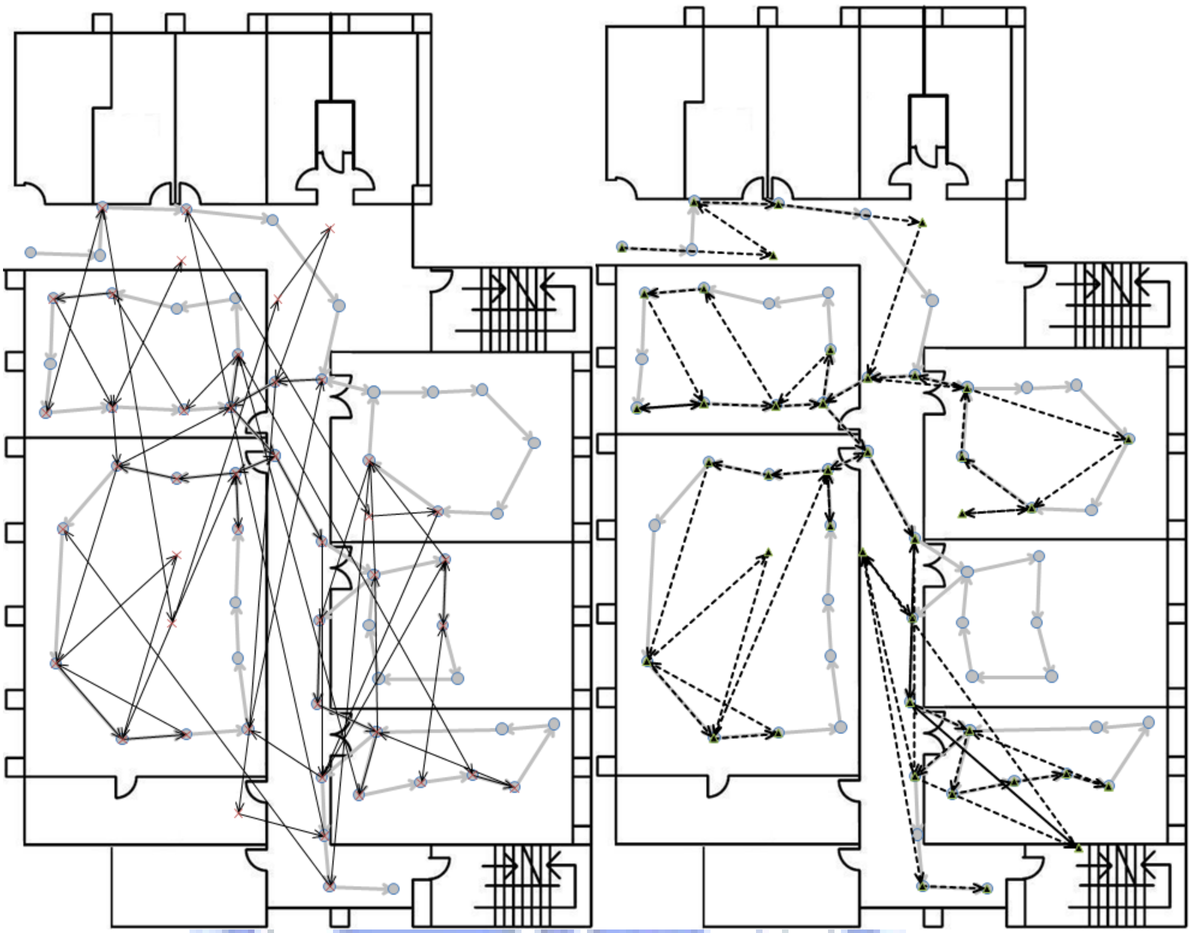
(a) (b)



(c) (d)

Fig. 30. The partial graphics of predicting path: (a)the lower half graph using NNSS, (b) the lower half graph using NNSS with trigger, (c) the upper half graph using NNSS, (d) the upper half graph using NNSS with trigger

Fig. 31 displays another moving path to show differences in our system and traditional pattern matching technique. The average error distance is 4.44m and the hit rate is 73% when we use traditional pattern matching method (NNSS). The average error distance is reduced to 2.21m and hit rate is increased to 89% when we use our system.



(a) (b)

Fig. 31. Another graphics of predicting path: (a)NNSS, (b)NNSS with trigger

From the above figures, we can view some features:

- Our method can increase the probability of determining the correct room.
- Reduce the emergence of long distance jump
- In general, average error distance will be improved.
- In one room, the positioning of the results is not necessarily completely correct.

5.2.2 Error Distance and Hit Rate

In Fig. 32, we design five different moving paths to observe the situation of positioning and each moving path at least through a trigger. The design chart and the detailed operation of graphics are shown in Fig. 33. In these figure, the gray line is original moving path, the thin line is drawn by basic pattern matching (NNSS) predicting results and the dotted line is the amended results of our trigger system.

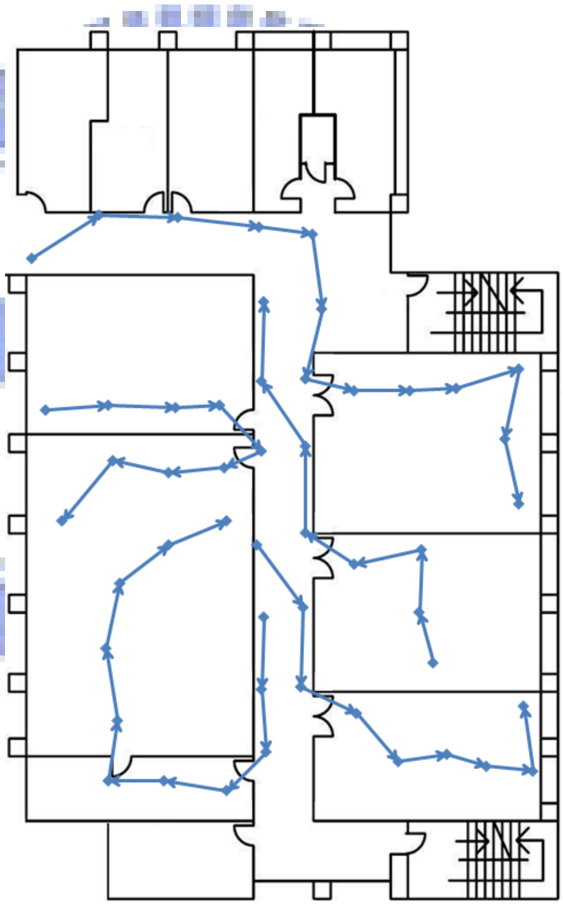
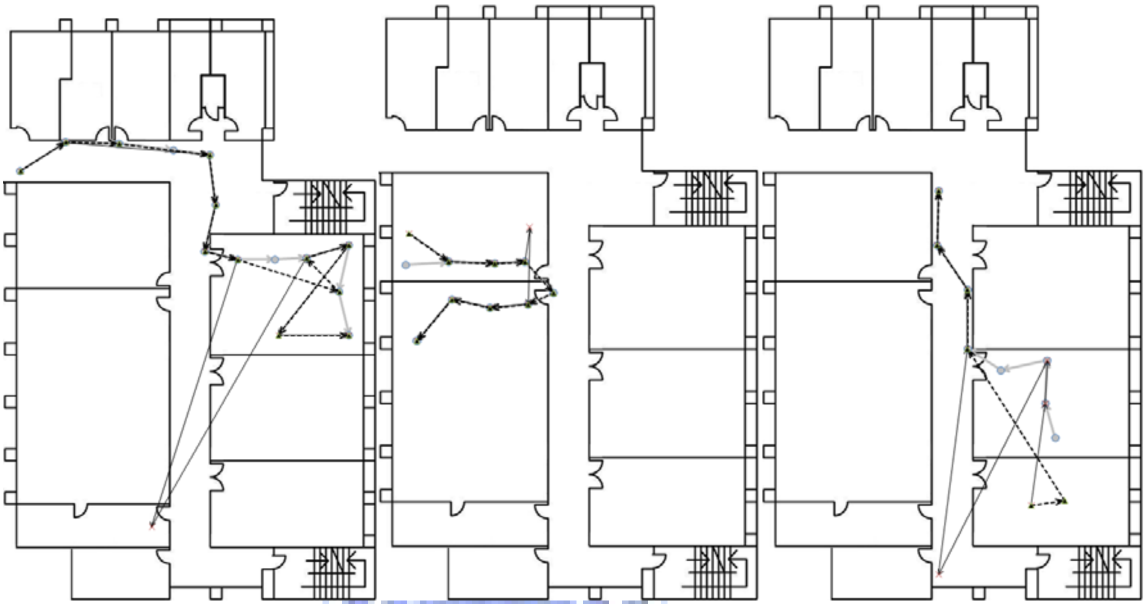
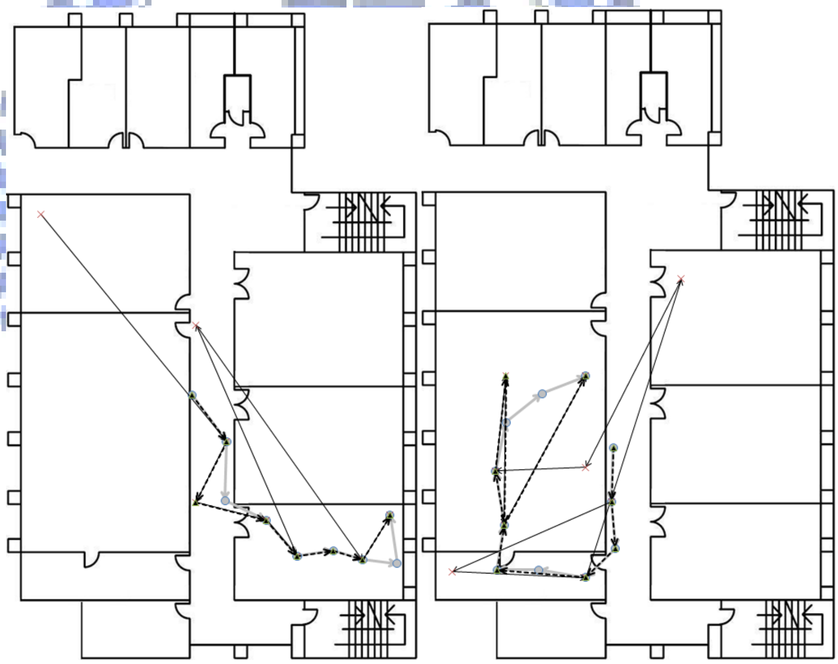


Fig. 32. Five testing moving path



(a)path 1 (b) path 2 (c) path 3



(d) path 4 (e) path 5

Fig. 33. The detailed operation of testing results

After calculation, the error distance of each path is shown in Fig. 34. Apart from other paths other than path 3 have accurate judgment in area transferring. Correct regional locking will be improved error distance obviously. The path 3 occurs incorrect regional locking. The increasing in error depends on the area decision.

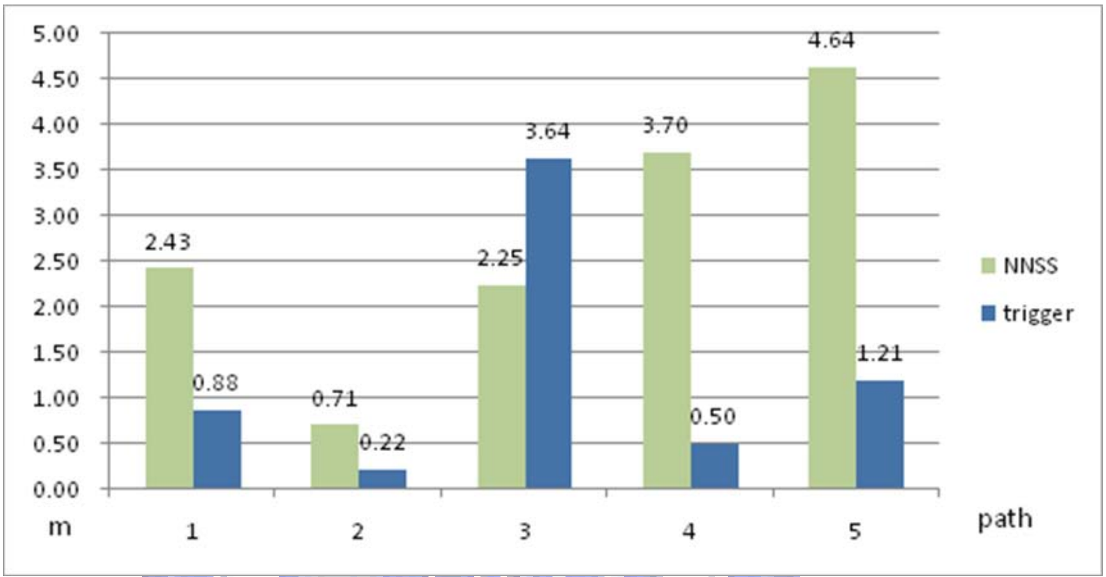


Fig. 34. The error distance in five paths using NNSS and NNSS with trigger

Fig. 35 shows the area's hit rate. The path has correct regional judgment will hit in right area. When the determination has an error, the overall results may be worse than the original.

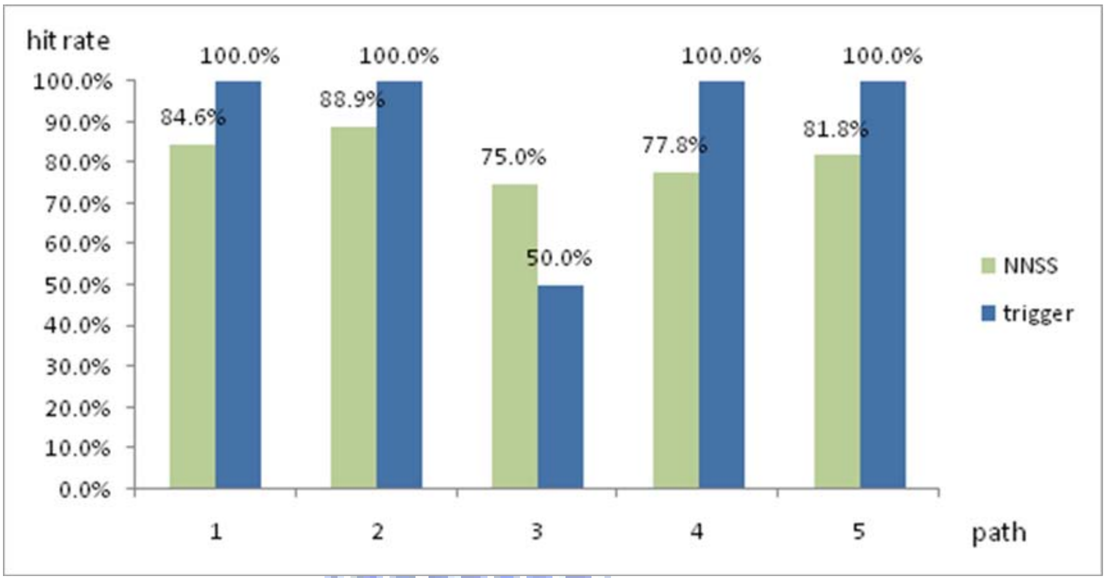


Fig. 35. The hit rate in five paths using NNSS and NNSS with trigger

From the above experiment, we can see that the majority of cases, our system can have better performance than traditional pattern matching system (NNSS). Especially in the unstable signal environment, our system has better performance. According to simulation and experiment results, we know our room-based localization system is workable.

Chapter 6

Conclusions

6.1 Conclusions

In the paper, we presented an efficient room-based localization system to focus on pattern-matching localization algorithms. With the aid of triggers, the positioning point can be restricted in a room. The room-based localization system can be used in particular place. In many situations, the room is more important than real position. It costs less time and resources to find a room than a position. Our experiments shows that we can start to position after one seconds when trigger event occurs and costs a few seconds to complete positioning.

6.2 Future Work

In future work, we will improve our system to increase the accuracy. In restricted track, it can make the effect to reduce training files. It is a valuable problem to discuss. Badge's power saving is another interesting problem to research.

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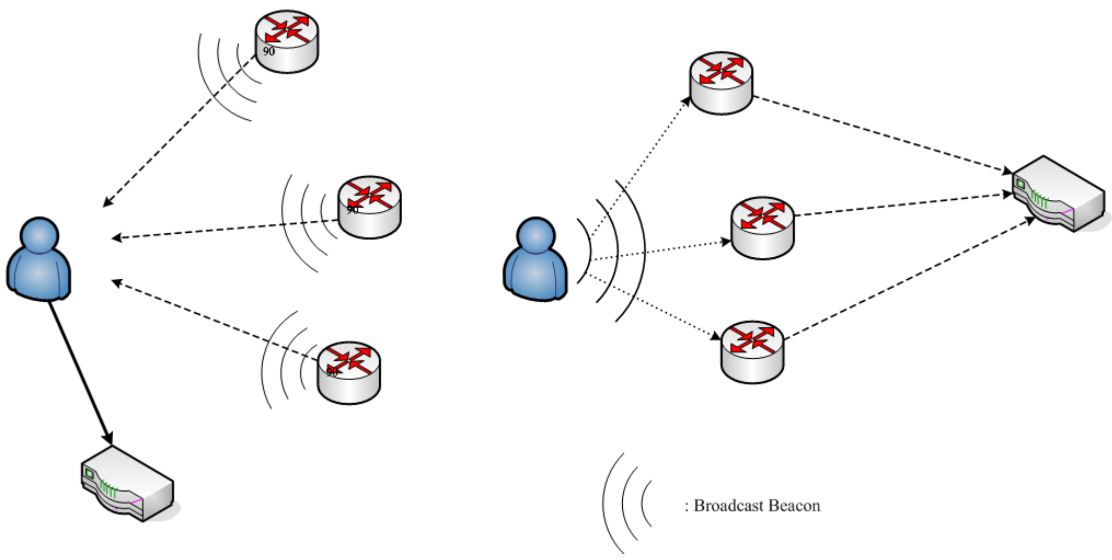
Appendix

Power Saving Mechanism

Fig. A is shown the difference beacon mechanism between our system and traditional system. The user carries a badge. Fig. A(a) is the traditional system. Badge receives short address and RSSI from routers and transfers to coordinator. Fig. A(b) a simple sketch map of our system. Badge broadcasts beacons voluntarily and be received by routers. A router will send a packet to coordinator when it gets a beacon. The most important difference of two systems is badge's action. In Fig. A(a), there are many packets (including beacons, triggers…etc.) to be received by badge in any time, so the badge needs to wake in all time. In Figure 8(b), badge only need to send beacons periodically and be woken up by trigger signal. In other time, the badge system can enter a half sleep mode. In addition to trigger's receiver, it will turn off all system power.



(a) Traditional beacon mechanism (b) Active beacon mechanism

Fig. A. The beacon mechanism between our system and traditional system

According to see Fig. B, we have more clear opinion to know the difference of two mechanisms.

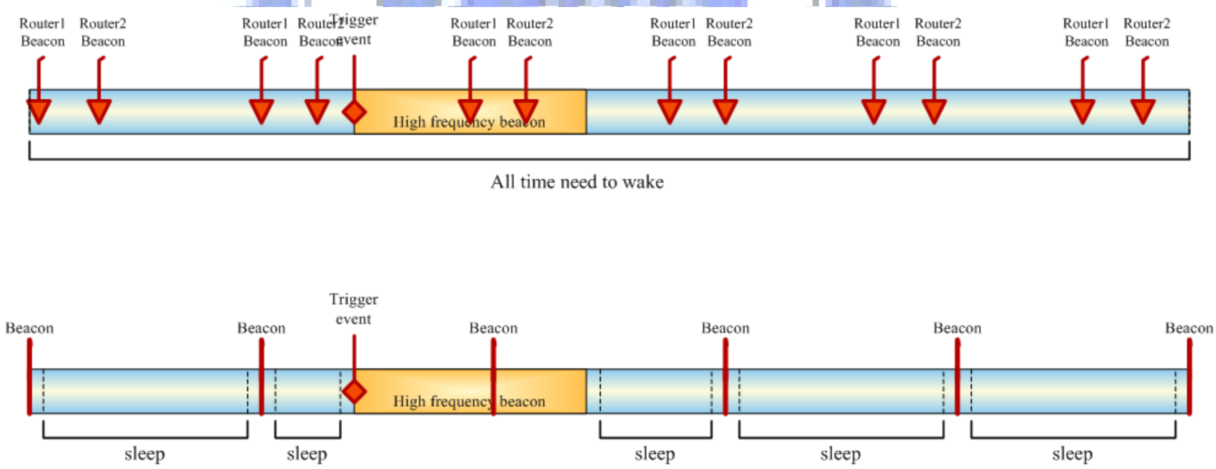


Fig. B. The beacon mechanism between our system and traditional system

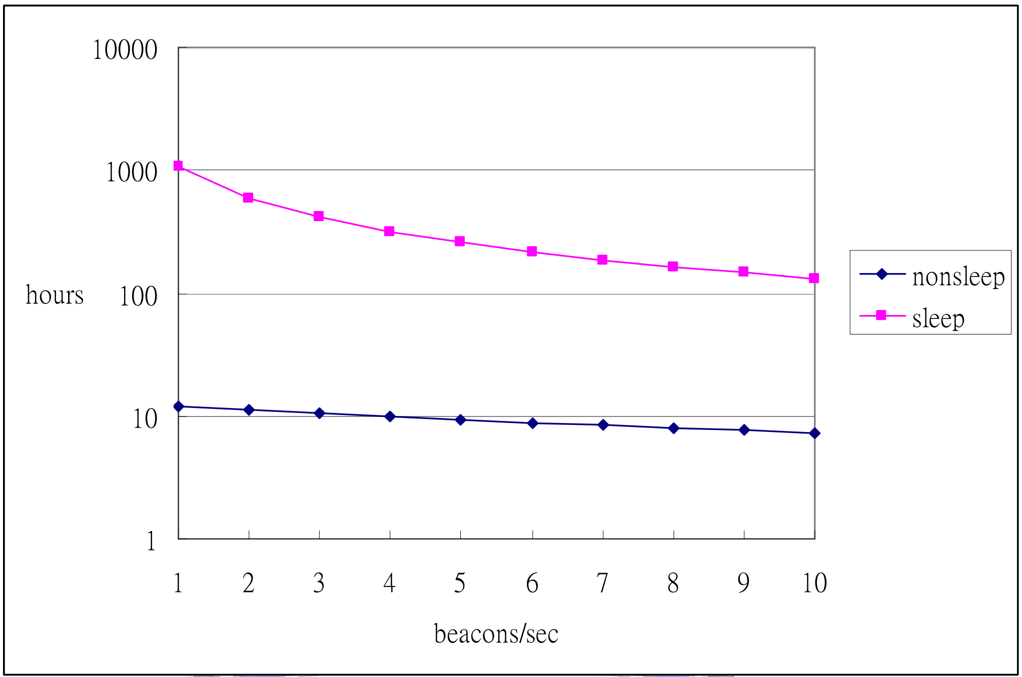


Fig. C. Simulation: The staying power of our system and traditional system.

From Fig. C, we know a system with sleep mechanism will increase 10-100 times staying power. It is very important in a mobile device.

The actual working time in badge is about 1/3-2/3 of simulating number. It is not very stable in real experiment result, because a battery's capacity is not fixed. It is influence on temperature, humidity, short time current…etc. Fig. D is shown the average staying power in real system.

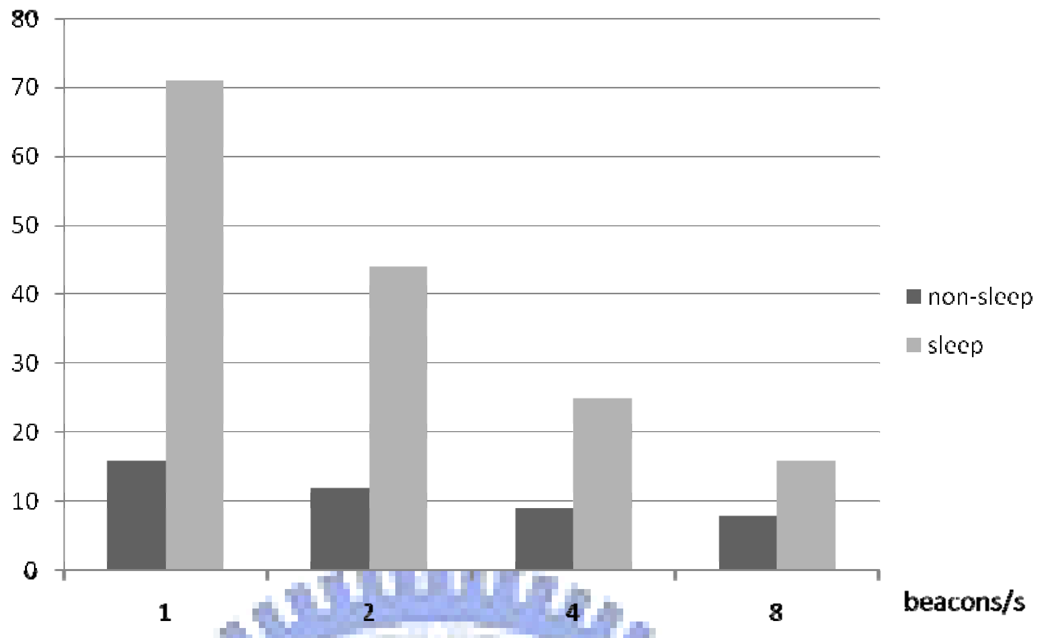


Fig. D. The average staying power in real system.